Issue Brief 13

Reimagining Healthcare Teams: Leveraging the Patient-Clinician-AI Triad To Improve Diagnostic Safety

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Introduction

Teamwork in healthcare is important to patient safety, including in the area of diagnosis. Consider the following scenario:

> *Ms. Hopkins is a 72-year-old woman with hypertension presenting to the office for her yearly checkup. On three occasions over the past month, her smart watch alerted her to an "abnormal heart rhythm." She did not contact your office because she was asymptomatic during the episodes. In addition, she "doesn't trust the watch's ability to diagnose heart problems."*
>
> *An electrocardiogram is completed during the visit and is normal. Ms. Hopkins notes that her older sister has atrial fibrillation. She would like to know if additional testing should be completed for atrial fibrillation.*

The call for adoption of team-based care models began more than a decade ago. In a 2012 Institute of Medicine (IOM) report, Mitchell, et al.,[1] defined team-based healthcare as:

> *…the provision of health services to individuals, families, and/or their communities by at least two health providers who work collaboratively with patients and their caregivers—to the extent preferred by each patient—to accomplish shared goals within and across settings to achieve coordinated, high-quality care.*

The 2015 National Academy of Medicine report Improving Diagnosis in Healthcare emphasized the importance of collaboration and teamwork among and between healthcare professionals, patients, and their families to reduce diagnostic errors.[2]

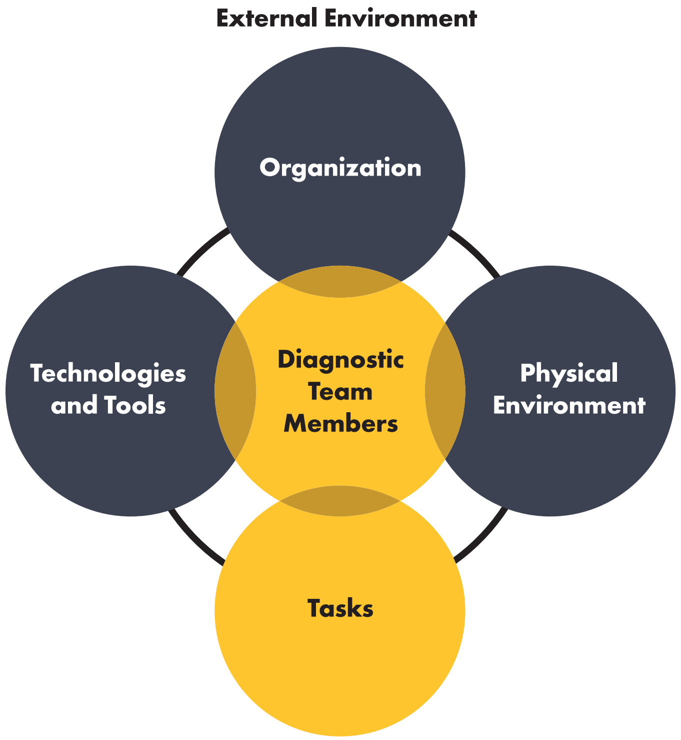
Definitions of team-based care and descriptions of core members of diagnostic teams generally include humans only, with technology serving as an ancillary tool.[2] In recent years, however, significant progress has been made in artificial intelligence (AI) and machine learning (ML) in the context of healthcare. AI is the use of computers to perform tasks that typically require objective reasoning and understanding. ML is a subdomain of AI that involves using computational methods to teach computers to learn from examples.

Some of the most significant healthcare AI/ML advancements have occurred in diagnostics. AI/ML is increasingly demonstrating safety and effectiveness in healthcare as suggested by the growing number of U.S. Food and Drug Administration (FDA) approvals.[3] For example, the FDA has approved ML models that can accurately diagnose breast cancer on mammograms, skin cancer on clinical images, and diabetic retinopathy on fundoscopic images.[4-6]

Incorporating AI/ML into broader clinical practice will undoubtedly affect healthcare teams and the patient-clinician relationship. As AI/ML with varying levels of autonomy becomes more common in healthcare, clinicians and patients will need to learn to effectively team with AI in the diagnostic process.

The diagnostic process occurs within a complex system that includes team members functioning in an interrelated fashion (Figure 1).[2] Diagnostic teams are often interprofessional and interdisciplinary.[1] However, how AI fits into the diagnostic team and affects the patient-clinician relationship still needs to be better defined. For example, patients and clinicians will need to understand their respective responsibilities when AI is involved in the diagnostic process. Furthermore, AI systems must be developed and implemented in a way that supports the patient-clinician diagnostic team, rather than hindering it.

Figure 1. Work system in which the diagnostic process takes place



Source: Adapted with permission from National Academies of Sciences, Engineering, and Medicine. Improving Diagnosis in Health Care. Washington, DC: The National Academies Press; 2015.

This issue brief provides a framework for patients and clinicians to successfully partner with safe and effective AI when making diagnostic decisions. At times this partnership will involve a tridirectional exchange among patients, clinicians, and AI that is not typically seen with tools and technologies used in healthcare.

Rather than viewing AI as a diagnostic tool to be wielded by human agents, we view it as a member of the diagnostic team capable of understanding, interpreting, reasoning, relating, responding, and ultimately collaborating with clinicians and patients in the diagnostic process.[7] The following sections describe the strengths and limitations of the dyadic relationships between patients and clinicians, patients and AI, and clinicians and AI. Finally, using the team-based care framework, we describe the triadic patient-clinician-AI diagnostic team.

The Patient-Clinician Dyad

The patient-clinician relationship remains central to the success of diagnostic teams. Patient-clinician dyads have been associated with advantages for both patients (e.g., improved quality of life, satisfaction with care) and clinicians (e.g., higher quality of care, better job satisfaction).[8-10] However, patients and clinicians face multiple challenges to developing strong relationships.

First, not all patients have access to clinicians, either at all (e.g., inadequate access to primary care) or when in need (e.g., urgent care that may result in overuse of emergency departments). When clinicians are available, they may have insufficient time to probe all aspects of a patient's history or to consider all potential data points to develop high-quality diagnostic or therapeutic plans.[11] The expanded use of telemedicine increases access for some patients but also reduces opportunities to incorporate physical examination findings into diagnostic decision making.[12]

Opportunities exist for AI to offer solutions that address some of these barriers and perhaps even strengthen the patient-clinician relationship.

The Patient-Artificial Intelligence Dyad

The emerging patient-AI relationship is largely a result of the rising adoption of wearable devices and the improved sensor capabilities of smart devices (mobile phones, watches, fitness bands, etc.). More than 300,000 healthcare applications are available in app stores.[13]

Some apps use AI/ML technology and are available without the need for a prescription from a licensed healthcare provider. This direct-to-consumer marketing of healthcare technology is a growing industry that will likely impact the patient-clinician relationship.[14]

Some early adopters of wearables and healthcare applications have been healthy individuals with an interest in quantifying their physiological signals (referred to as the "quantified self"). But more recent consumer-oriented wearables are targeting use cases related to medical diagnosis. For example, Apple has received FDA approval for wearable (Apple Watch) AI-based technology that notifies users of the presence of atrial fibrillation and how frequently they are in atrial fibrillation.[15, 16]

These types of technologies not only offer the opportunity to monitor patients and gather data outside of scheduled office visits (home, work, etc.) but also may permit early detection and treatment to avoid negative patient outcomes (e.g., thromboembolic stroke). This out-of-office monitoring could provide reassurance to some patients but may cause unnecessary anxiety for others. Each individual patient responds in a way that will lead to more or less concern and subsequent contact with the health system related to AI output.

While technologies such as the Apple Watch can provide accurate diagnoses and useful data (e.g., burden of atrial fibrillation), they have drawbacks. In many cases, they do not individualize a patient's risk, consider patient-specific contextual factors, or address patients' specific concerns about diagnosis and treatment.

For example, atrial fibrillation can be asymptomatic or symptomatic, can be chronic or paroxysmal, and can occur in the presence or absence of valvular heart disease. For a young male patient with no other risk factors, nonvalvular atrial fibrillation confers a 0.2 percent annual risk of stroke.[17,18] For an older female patient with all possible risk factors, the annual risk of stroke is more than 10 percent in nonvalvular atrial fibrillation.

Although two such patients may be given the same advice of "talk to your healthcare provider" in response to AI-suspected atrial fibrillation, the urgency of this advice differs depending on the medical context. These examples also highlight the potential for patients to experience unwarranted reassurance or alarm due to AI output. More specifically, it allows an appreciation of the role of competent clinicians in interpreting AI output with consideration of patients' full context.

The patient-AI dyad offers benefits, but gaps remain that for the time being are most effectively addressed by a clinician capable of serving as a liaison in the patient-AI relationship.[19]

The Clinician-Artificial Intelligence Dyad

Patients interact with their primary care provider infrequently or periodically at best, which results in infrequent measurements that provide only a snapshot of an individual's health. Sample rate aside, these measurements may be plagued with bias or error (e.g., white coat syndrome or missing context).[20] In light of these limitations, technology for measuring physiological signals has been developed for at-home use (e.g., Holter monitors) and is used for diagnosing a range of health issues.

AI promises to help process, organize, and transform these data into actionable knowledge.[21] We have seen examples of algorithms that can automatically process hundreds of thousands of heartbeats in seconds[22, 23] and others that can automatically track falls.[24] As wearables and sensors become more common in daily living, they will provide a more complete picture of an individual's daily activities and, in turn, their health.

However, data from wearables will fail to have impact if they are not effectively integrated into clinical care. Relevant information must be extracted from signals and presented to clinicians (and patients) in a way that is actionable. The field of human-AI (and more specifically clinician-AI) interaction is relatively new.

Numerous research questions need to be addressed and implementation challenges need to be overcome. For example, given an algorithm for estimating atrial fibrillation burden based on data collected from wearables, how often should this information be conveyed to a clinician? The low frequency of primary care visits might defeat the purpose of continuous monitoring. Instead, we might consider a scenario in which the patient is monitored continuously and the clinician alerted when the AI has identified new *actionable* knowledge.

Once the AI alerts the clinician, how should these data be presented? As new data streams come online and are integrated into the electronic health record (EHR), we will also require education around what actions might be considered appropriate based on the data. For example, an AI system is designed to diagnose atrial fibrillation and make recommendations about anticoagulation based on its calculation of the CHA_2DS_2-VASc score. This score is a clinical prediction rule (CPR) that estimates the risk of stroke in patients with atrial fibrillation. The system also uses the HAS-BLED score, a CPR that estimates a patient's risk of major bleeding. Use of this system could result in significant practice variation depending on clinicians' comfort with the algorithm and their subsequent uptake of the algorithms' recommendation.[25]

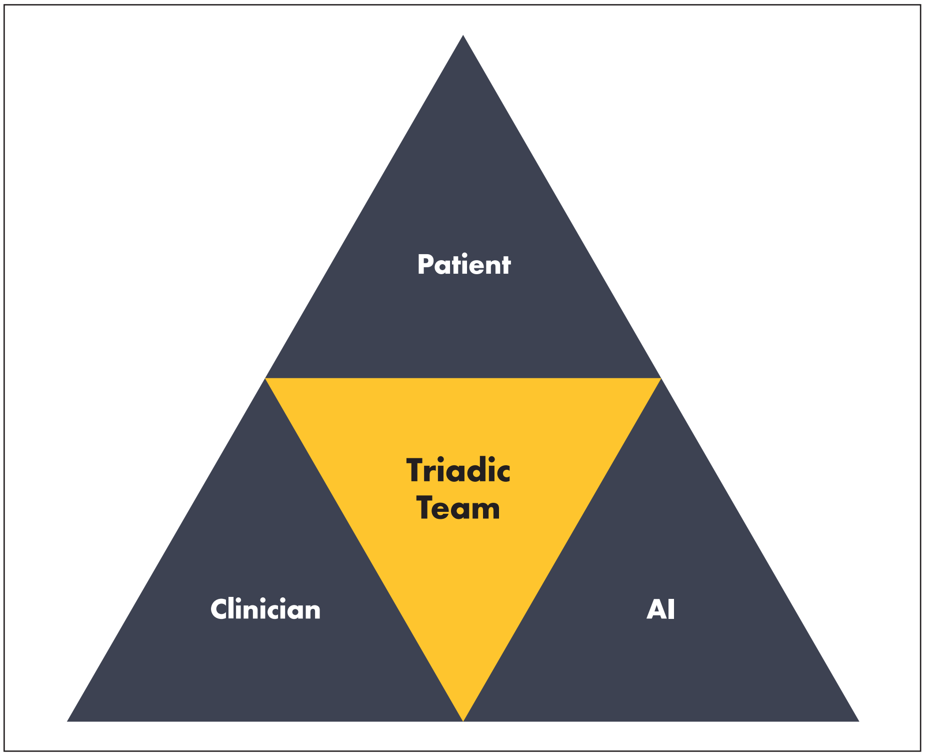
While promising, the clinician-AI dyad relies on both the strength of the clinician-patient relationship and the patient-AI relationship. If clinicians do not have a strong rapport with patients, it will be difficult to identify AI "blind spots" (i.e., settings in which the AI fails). Moreover, it may be difficult to convince patients to follow through with recommended diagnostic plans that come directly from AI. If the patient does not have a strong relationship with AI and does not engage with the AI (e.g., does not charge/use the wearable sensors), then AI may offer limited utility.

Even so, AI has the potential to recognize and account for limitations in the clinician-patient relationship (e.g., recent work in using AI to coach clinicians on their use of language and in motivational interviewing).[26, 27] In addition, if the clinician-patient relationship is strong but the patient-AI relationship is weak, the AI might lean on the clinician-patient relationship to motivate change in patient behavior toward AI. For example, if a patient is unresponsive to alerts or notifications from a wearable AI-based device, AI might ask the clinician to encourage the patient to increase responsiveness or to take the action the AI recommends.

The Patient-Clinician-Artificial Intelligence Triad

As described above, each member of dyadic diagnostic teams brings their unique perspective and skill set to address a diagnostic problem. Each of these dyads has clear benefits and limitations. The confluence of the dyads to form the patient-clinician-AI (PCA) triad may address some of the gaps left by any of the dyads alone (Figure 2).

Figure 2. Patient-clinician-AI diagnostic team



With the proliferation of AI algorithms that may inform diagnostic decision making, the structure and function of diagnostic teams are changing. For example, clinicians are receiving support from models integrated into the EHR, such as the Targeted Real-time Early Warning System (TREWS) for sepsis. A recent study of clinicians engaging with TREWS showed that clinicians perceived the system as playing a supportive role both in and beyond diagnosis.[28]

Clinicians will not only use AI-based diagnostic decision support embedded in EHRs, but, similar to the scenario in the Introduction, will also interact with patients who have healthcare applications that use AI algorithms. Therefore, clinicians must begin to consider how AI will inform their diagnostic decision making and how this new partner will impact their relationships with patients.

Core Principles for the PCA Diagnostic Team

Ideally, members of the PCA diagnostic team will support and augment each other's performance. As diagnostic PCA teams are envisioned, we recommend extending the team-based healthcare principles IOM proposed to include AI as a member of the diagnostic team. These principles include establishing shared goals, clear roles, mutual trust, effective communication, and measurable processes and outcomes (Table 1).[1]

Table 1. Principles for patient-clinician-AI diagnostic teams

Principle	Definition	Patient/ Caregiver	Clinician	AI
Shared goals	The team, including the patient and, where appropriate, family members or other support people, works to establish shared goals that reflect patient and family priorities and can be clearly articulated, understood, and supported by all team members.	The patient and their family member or other support person inform the clinician about a health problem. They describe this concern within the patient's context and express the patient's values, preferences, and circumstances.	The clinician validates the concern of the patient, family member, or other support person. The clinician agrees to partner with the patient/ family/support person to develop a plan to diagnose and treat the patient's health problem.	The clinician recommends using an AI-based algorithm developed to evaluate the patient's health problem.
Clear roles	Clear expectations for each team member's functions, responsibilities, and accountabilities optimize the team's efficiency and often make it possible for the team to take advantage of division of labor, thereby accomplishing more than the sum of its parts.	The patient and their family member or other support person agree to report new updates related to the patient's status. They also agree to enable the AI-based application and ensure that it is used as recommended.	The clinician uses data from the patient's history, physical examination, test results, and AI algorithm to diagnose the patient's health problem. The clinician will incorporate the patient's values, preferences, and circumstances to provide recommendations for testing and treatment. The clinician is responsible for ensuring that roles are clearly defined.	The AI-based algorithm runs as expected when the device is used. It provides daily summaries and notifies the patient, family, and clinician of relevant events.
Mutual trust	Team members earn each other's trust, creating strong norms of reciprocity and greater opportunities for shared achievement.	The patient and their family member or other support person have rapport with the clinician. The patient trusts that the clinician and AI will effectively complete their assigned tasks (e.g., taking a careful history and physical examination, monitoring, estimating risks, predicting outcomes, developing an evaluation and treatment plan consistent with their values and preferences) to aid the diagnostic process.	The clinician has reviewed the safety, validity, and reliability of the AI-based application. In addition, the clinician has successfully used the application for other patients. The clinician trusts that the patient, family, other support person, and AI can effectively complete their assigned tasks (expressing values and preferences, completing recommended diagnostic testing, monitoring, reporting status changes, etc.) to aid the diagnostic process.	The AI relies on patients, family or other support people, and clinicians to complete their assigned tasks (wearing the technology, ordering tests, having tests completed, interpreting model output, etc.).

Principle	Definition	Patient/ Caregiver	Clinician	AI
Effective communication	The team prioritizes and continuously refines its communication skills and has consistent channels for efficient communication.	The patient and their family member or other support person communicate with the AI by providing data (e.g., via wearable device) needed to estimate risk and identify events. The patient and their family member or other support person provide status updates by communicating with the clinician (or other members of the healthcare team) in-person, virtually, or electronically.	The clinician (and other members of the healthcare team) efficiently and effectively respond to the patient's status updates and questions. The clinician may also serve as the liaison between patients, their family members, other support people, and the AI. Clinicians use shared decision making that integrates patient values, preferences, and circumstances.	The AI receives input from patients and clinicians to generate outputs that aid the diagnostic process. The AI clearly communicates its outputs to patients, their family members or other support people, and clinicians in a timely fashion that does not negatively impact lifestyle or workflow.
Measurable processes and outcomes	Reliable and ongoing assessment of team structure, function, and performance is provided as actionable feedback to all team members to improve performance.	The patient and their family member or other support person provide regular updates related to the perceived utility and feasibility of the diagnostic plan (e.g., barriers to having testing completed, barriers to using AI).	The clinician must regularly evaluate the risks and benefits of the team's structure and function. The clinician should receive feedback from patients about the team's structure and effectiveness. Clinicians should become comfortable communicating feedback about a diagnostic model's utility to developers and health system leadership.	Continued monitoring by the model may provide updates about the patient's status after an intervention designed to address the health problem is implementated. AI outputs may include the frequency and duration of patient or clinician use of the application.

Shared Goals

In PCA teams, the process of establishing diagnostic goals moves from a bidirectional exchange between the patient and the clinician to a tridirectional exchange. In a tridirectional exchange, patients and clinicians receive information from AI systems, AI systems receive information from patients and clinicians, and patients and clinicians receive information from one another.

Each member of the PCA diagnostic team brings their own unique goals to the relationship. For example, clinicians' goals may include providing safe, efficient, evidence-based care. Likewise, AI algorithms are ideally designed with the goal of effectively performing specific tasks (e.g. recognizing an arrhythmia), often with little consideration of the patients' or clinicians' context.

The patient's values, preferences, and circumstances should provide the foundation on which team goals are established. Patients, their families, or other caregivers must be comfortable describing their unique situation and their wishes. Clinicians should be adept at patient-centered communication to effectively guide these conversations. In addition, AI should be designed and deployed in a way that is conducive to meeting specific diagnostic goals. Ultimately, clinicians will be responsible for ensuring that the goals of each team member are carefully considered and that the team's shared goals coalesce around patients' values, preferences, and circumstances.

Clear Roles

Clear, specific delineation of roles within the PCA team is essential to the team's success. In most cases, the diagnostic process is triggered when a patient notes a specific sign or symptom and notifies their healthcare provider. Increasingly, the diagnostic process may be triggered by patients wearing direct-to-consumer AI-based technologies.

Ideally, these AI alerts will lead to the patient engaging with the healthcare system and providing the information needed for accurate and timely diagnosis and treatment of their health concern. For instance, a patient may be notified by their smart watch (AI role) that they are experiencing tachycardia or an abnormal heart rhythm, which leads to the patient notifying their healthcare provider (patient role). In this situation, a clinician would need to be familiar with the validity, reliability, and intended use of the AI algorithm and the patient's context to determine the need for additional evaluation (clinician role).

Another use case involves the clinician recommending a specific wearable or other AI-based technology to perform a specific task (e.g., information gathering, integration of information,) for diagnostic purposes. For example, a clinician may recommend a wearable technology to assess a patient's fall risk.[29] The patient, family member, or other caregiver would be responsible for ensuring the technology is worn, while the AI would provide daily summaries about fall risk and near falls and notify family members or the clinician if a fall occurs. This information could lead to interventions to prevent falls.

While patient and clinician autonomy should be preserved, AI will have variable levels of autonomy depending on the diagnostic problem. In addition, clinicians and patients will have varying levels of comfort with the level of autonomy assigned to AI systems. For example, in some cases AI will provide a diagnosis independent of a clinician. The AI-based IDx-DR system, which autonomously diagnoses diabetic retinopathy without clinician overreading, is an example of a fully autonomous model.[30]

Alternatively, an algorithm may alert clinicians to an increased probability of a diagnosis, leading to more efficient triage and diagnosis of a problem. For instance, an AI-based system designed to identify intracranial hemorrhage on CT images may lead radiologists to prioritize earlier reading of CT scans designated as high risk.[31]

Finally, we acknowledge the rapidly evolving field of AI. Patients, clinicians, and developers will need to be nimble and capable of adapting as roles are likely to change. For example, referring to the previous example, one can imagine AI directly notifying the clinician of actionable information (responsibility moves from the patient to AI), leading to more efficient diagnosis. This type of change may require an adjustment of processes and workflow to accommodate the new stream of information from a different source that is presented in a different way and perhaps at different times.

Mutual Trust

Assigning roles may prove futile if trust between team members is not established. Within the PCA triad, mutual trust is needed between patients and clinicians, and patients and clinicians need to trust the AI system's ability to meaningfully contribute to the diagnostic process. How to establish trust between AI and patients/clinicians is an area of active research.[32, 33]

Rojas and colleagues suggested that clinician trust in AI be informed by the system's fairness, transparency, and performance.[34] To this end, the Office of the National Coordinator for Health Information Technology recently proposed the HTI-1 rule, which would require users of clinical decision support systems using AI to have access to answers to three basic questions[35]:

1. What data were used to train the algorithm?
2. How should the predictive algorithm be used, updated, and maintained?
3. How does the algorithm perform using fairness metrics in testing and in local data, if available?

As described above, in some cases clinicians will introduce diagnostic AI algorithms to patients. In other cases, patients will bring new AI-based technologies to clinicians. Regardless of the initiator, clinicians will need to develop the skills to critically evaluate AI-based diagnostic systems and make recommendations about their use. Thus, prospective studies are needed that demonstrate AI systems' reliability, validity, and positive effect on important patient outcomes.

As with other healthcare interventions, patients are unlikely to adhere to plans that include AI if they do not trust the provider recommending the technology or do not trust the technology itself. These feelings may be especially common among historically marginalized groups.[36, 37] Biased algorithms can worsen health inequities, as described by Obermeyer and colleagues. They showed that a widely used algorithm demonstrated signficant racial bias, as it disproportionately recommended additional assistance for White patients compared with Black patients, despite Black patients being sicker.[38] To mitigage bias and increase patient trust, rigorous strategies must be used during the development and implementation of algorithms.[39]

Similarly, clinicians will need to trust that AI-based technologies are safe and effective before recommending them to patients. In addition, clinicians must trust that patients are experts about their experiences, context, and values.[40] Effective communication between all team members will be essential to developing the mutual trust needed for optimal functioning of the PCA team.

Clinicians will need education and training related to the use of AI/ML in the diagnostic process, which is beyond the scope of this brief. However, we acknowledge that they will need to become adept at appraising information describing AI/ML interventions, applying the output of diagnostic models, and communicating the role AI/ML played in the diagnostic process.[41] This education and training will also be essential to avoiding underreliance or overreliance on AI/ML in the diagnostic process.

Effective Communication

Communication between humans and AI comes in many forms. For example, patients may communicate with AI systems by speaking; entering text, photos, or other types of data into the system; or using wearable devices (e.g., smart watches) that provide continuous monitoring. The AI communicates by producing an output in the form of an alert, reminder, probability, diagnosis, recommendation, or intervention.

AI communication with patients will depend on its purpose, goals, and FDA classification. For example, non-FDA-regulated technologies should not provide a diagnosis and may instead provide an alert to a potential abnormality (e.g., bradycardia). Outputs of FDA-regulated technologies will depend on the risk classification of the technology, with higher risk models producing outputs within the context of high-risk situations (e.g., ML-based cardiac defibrillator).

In fall 2022, the FDA provided updated guidance on designation of software as a medical device (SaMD).[42] Previously, most EHR software did not meet SaMD criteria. However, this situation is changing as EHRs, hubs for healthcare communication, are increasingly incorporating AI-based predictive algorithms designed to augment diagnostic decision making.[34, 43]

Clinician interaction with diagnostic AI algorithms will most often occur via the EHR or patient-owned wearable devices. Developers and health system leaders should proceed with caution to avoid making an already overwhelming EHR workload unmanageable with the addition of AI. For example, clinicians could quickly become discouraged by AI if they open the EHR to find patient-generated data lacking clinical context for multiple patients. While the data may contain valuable diagnostic information, attention must be given to the form and frequency of presentation of these data.

Patients and clinicians should be able to seamlessly communicate with AI. Therefore, anyone developing or implementing these models should consider usability. Patients and clinicians are not likely to engage with these potentially useful technologies if they significantly disrupt lifestyle or clinical workflow, resulting in inconvenience and inefficiency. Furthermore, AI outputs should be presented to patients and clinicians at the right time, with appropriate frequency, in a clear, concise, and user-centered manner. Optimal output is likely to minimize alert fatigue, or desensitization to alerts, helping to avoid diagnostic errors that result from inappropriate or inadequate use.

Measurable Processes and Outcomes

Re-evaluation of the PCA diagnostic team structure and function should occur at regular intervals. Patients and clinicians may address this issue during followup visits or via patient- or clinician-initiated portal communications. Another option is to discuss the matter with other members of the healthcare team (e.g., nurses, medical assistants, pharmacists, care navigators).

Patients should have the opportunity to provide anonymous feedback to clinicians and healthcare organizations via patient satisfaction surveys. The team's effectiveness should be measured based on the shared goals set at the beginning of the diagnostic process. The team should consider the patient, clinician, and AI-related factors that positively or negatively impact the diagnostic process. When possible, team members should share thoughtful, constructive feedback with each other.

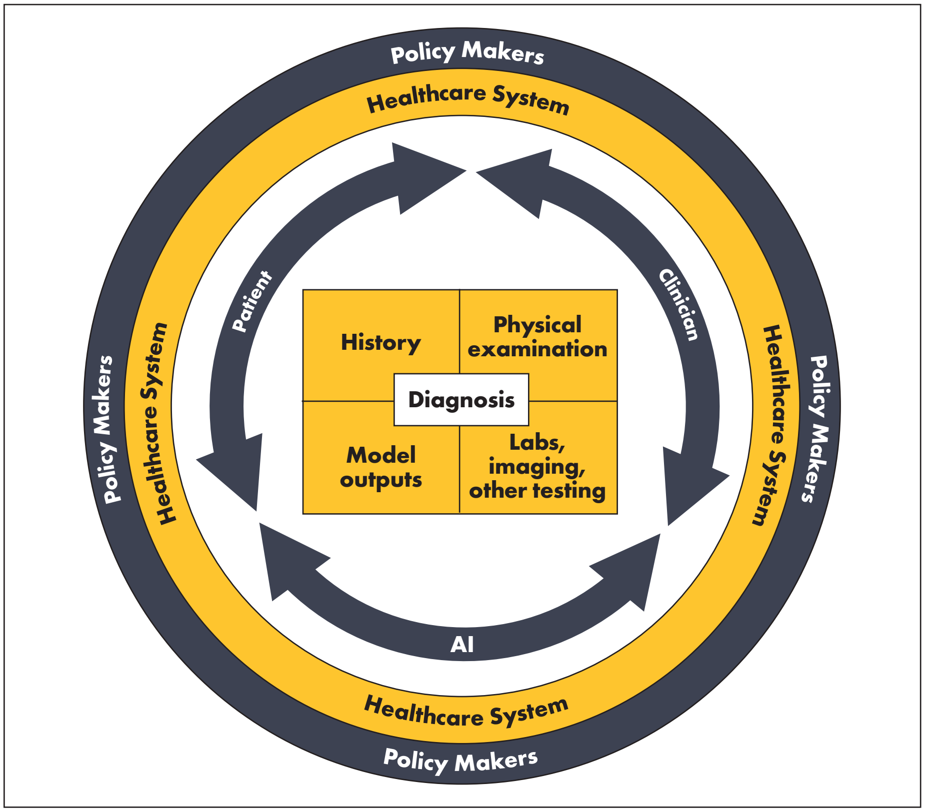
Clinicians should be comfortable communicating with health system leadership about AI performance. This feedback may lead to improvement of model performance and usability, as well as iterative updates similar to upgrades for EHRs. Ultimately, we imagine systems in which feedback can also be provided directly to the AI systems as it learns and adapts over time. Similarly, as alluded to above, AI might provide feedback to clinicians about how they might improve delivery of patient care.

The goal is for the diagnostic team's performance to be augmented by the collective contribution of each team member in a way that allows efficient and effective diagnosis of the patient's medical problem. Therefore, consistent with the diagnostic process, health systems and clinicians should learn from diagnostic errors, near-misses, and accurate, timely diagnoses that result from the PCA diagnostic teams.

Barriers

Several potential barriers must be addressed as AI algorithms are integrated into diagnostic teams. For example, liability in the event of a missed, inaccurate, or delayed diagnosis is an active area of discussion.[44] In addition, payer reimbursement strategies for the use of AI algorithms in the diagnostic process are evolving. Finally, attention must be given to the potential for historically marginalized individuals to be negatively impacted by biases perpetuated by algorithms and unequal access to effective algorithms. Addressing these challenges will require engagement from all members of the diagnostic ecosystem (Figure 3).

Figure 3. Diagnostic ecosystem: factors impacting diagnostic decisions



Conclusion

This brief builds on a team-based care framework by describing how AI may be integrated into the diagnostic team. We must think carefully about how to incorporate safe and effective AI into diagnostic teams. While the structure and function of PCA diagnostic teams have not been defined, AI is primed to become an essential member of diagnostic teams. Therefore, patients and clinicians will need to learn to leverage the benefits and understand the limitations of AI, instead of viewing it as a “third wheel” in their relationship.[45] As PCA diagnostic teams develop, it is useful to consider a framework for ensuring that these teams are high functioning and designed to meet the goal of improving diagnostic safety.

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